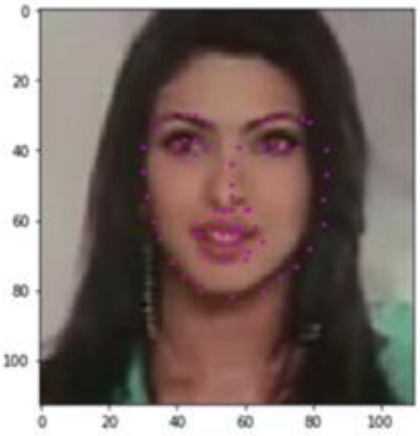
Introduction to Deep Learning (I2DL)

Tutorial 9: Facial Keypoint Detection

Overview

- Exercise 08: Case Study
- Fully Connected & Convolutional Layers
  - Recap
  - Changes to Dropout & BatchNorm
- Exercise 09: Facial Keypoint Detection



Exercise 8: Leaderboard

Exercise 1 | Exercise 3 | Exercise 4 | Exercise 5 | Exercise 6 | Exercise 7 | Exercise 8 | Exercise 9 | Exercise 10 | Exercise 11

#	User	Score	
1	u0741	100.00	CNN
2	u1289	100.00	MLP
3	u0736	99.00	
4	a0001	99.00	
5	u1770	96.00	
6	u1479	95.00	
7	u0922	94.00	
8	u0926	91.00	
9	u1662	90.00	
10	u1149	89.00	
11	u1625	88.00	
12	u0533	88.00	

Exercise 8: Case Study - Architecture

```python
self.encoder = nn.Sequential(
  nn.Linear(input_size, num_hidden),  # 784 -> 392
  nn.BatchNorm1d(num_hidden),
  nn.ReLU(),
  nn.Linear(num_hidden, int(num_hidden*0.5)),
  nn.BatchNorm1d(int(num_hidden*0.5)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.5), int(num_hidden*0.25)),
  nn.BatchNorm1d(int(num_hidden*0.25)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.25), int(num_hidden*0.125)),
  nn.BatchNorm1d(int(num_hidden*0.125)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.125), latent_dim))
```

```python
self.decoder = nn.Sequential(
  nn.Linear(latent_dim, int(num_hidden*0.125)),
  nn.BatchNorm1d(int(num_hidden*0.125)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.125), int(num_hidden*0.25)),
  nn.BatchNorm1d(int(num_hidden*0.25)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.25), int(num_hidden*0.5)),
  nn.BatchNorm1d(int(num_hidden*0.5)),
  nn.ReLU(),
  nn.Linear(int(num_hidden*0.5), num_hidden),
  nn.BatchNorm1d(num_hidden),
  nn.ReLU(),
  nn.Linear(num_hidden, input_size))
```

```python
self.classifier = nn.Sequential(
  nn.Linear(latent_dim, num_hidden_c),
  nn.BatchNorm1d(num_hidden_c),
  nn.LeakyReLU(),
  nn.Dropout(p=0.2),
  nn.Linear(num_hidden_c, num_hidden_c),
  nn.BatchNorm1d(num_hidden_c),
  nn.LeakyReLU(),
  nn.Dropout(p=0.2),
  nn.Linear(num_hidden_c, num_classes))
```

AE

```
# Paramters: Your model has 0.824 mio. params
```

CLS

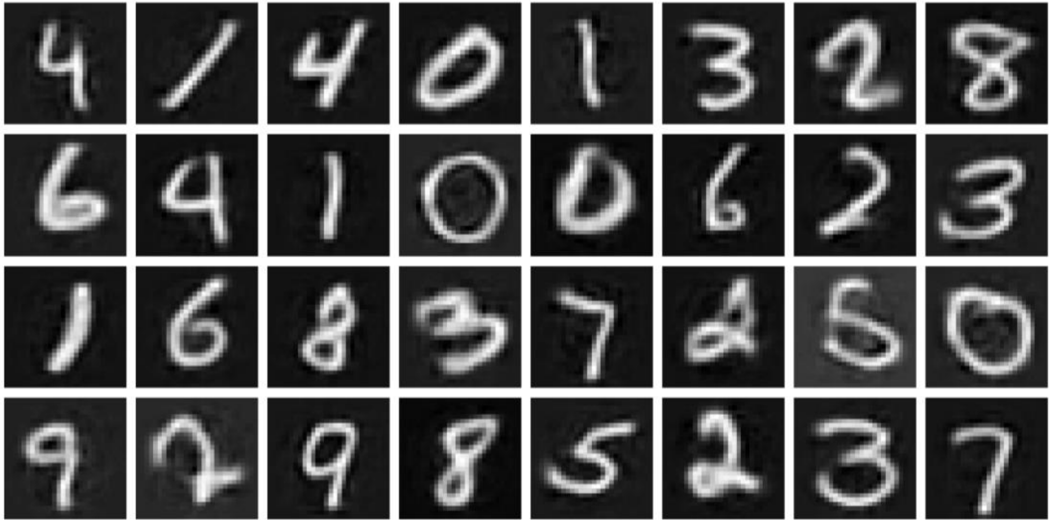
```
# Paramters: Your model has 0.591 mio. params
```

Exercise 8: Case Study – Hyper-Parameters

```
transform = T.Compose([
    T.RandomApply([T.RandomRotation(degrees=30)], p=0.2),
    T.RandomApply([T.GaussianBlur(kernel_size=3, sigma=(0.1, 1.5))], p=0.2),
    T.RandomApply([T.RandomAffine(degrees=0, translate=(0.08, 0.08))], p=0.2),
])
```

```
hparams = {
  "n_hidden": 392,
  "latent_dim": 32,
  "n_hidden_C": 400,
  "learning_rate": 5e-4,
  "weight_decay": 1e-4,
  "epochs_ae": 5,
  "epochs_classifier": 50
}
```

Auto-Encoder Reconstructions

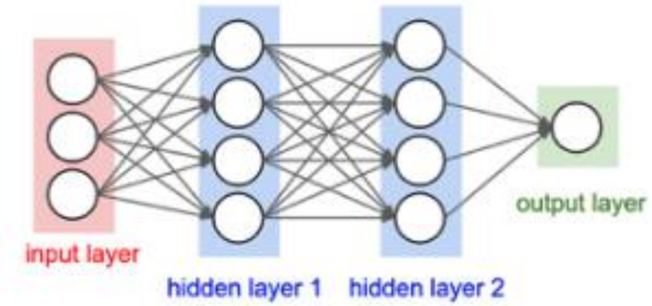


Fully Connected
vs
Convolutional Layers

Recap: Fully Connected Layers

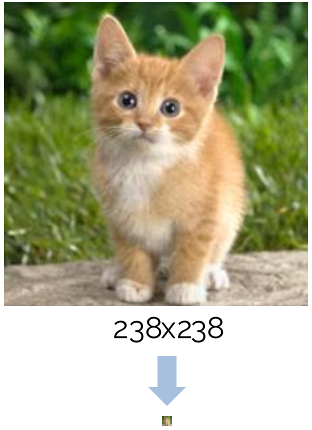
- **Fully Connected (FC) networks / Multi-Layer Perceptron (MLP):** Receive an input vector and transform it through a series of hidden layers (weights & activation functions).

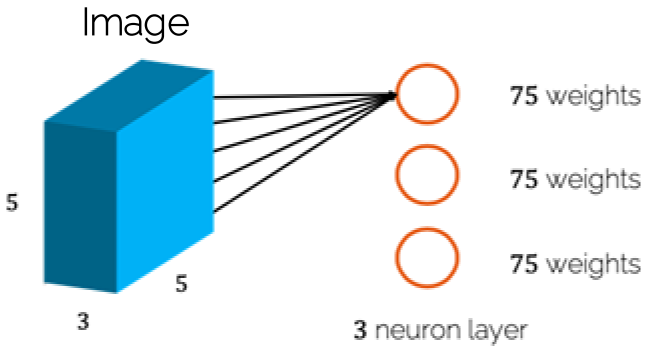
- **Fully Connected layers:** Each layer is made up of a set of neurons, where each single neuron is connected to all neurons in the previous layer

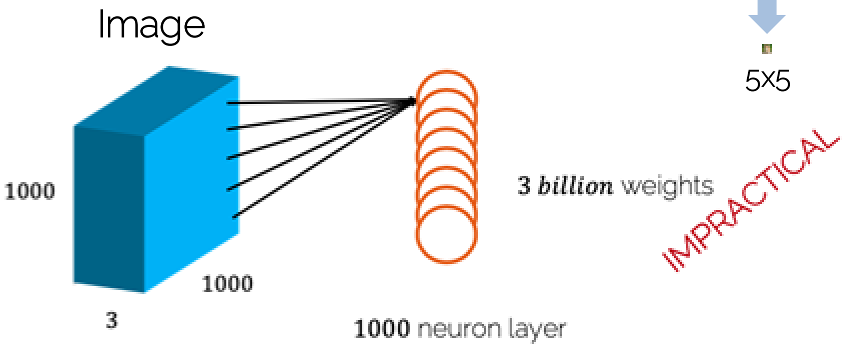


Computer Vision – MLP

- **Assumption:** Input to the network are images
- **Disadvantage:** Images need to have a certain resolution to contain enough information



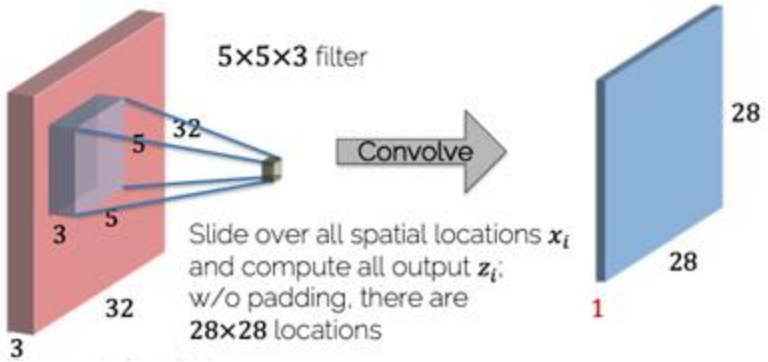




Can we reduce the number of weights in our architecture?

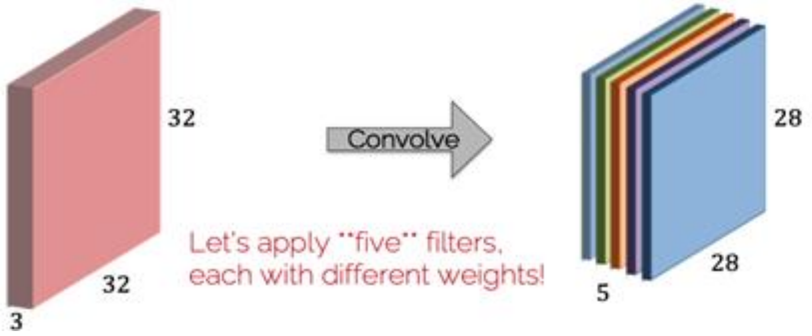
Computer Vision - CNN

- **Assumption:** Input to the network are images
- **Idea:** Sliding filter over the input image (convolution) instead of passing the entire image through all neurons individually



Computer Vision - CNN

- **Assumption:** Input to the network are images
- **Filters:** Sliding window with the same filter parameters to extract image features
- **Advantage:** Learn translation-invariant "concepts" and weight sharing



Convolution: Hard-coded

3x3 kernel

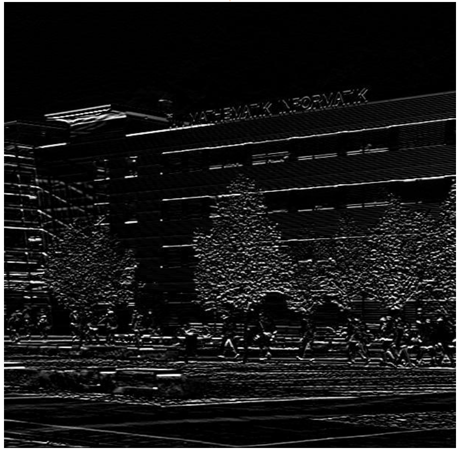
```
[-1, -1, -1]
[ 0,  0,  0]
[ 1,  1,  1]
```

*

*

3x3 kernel

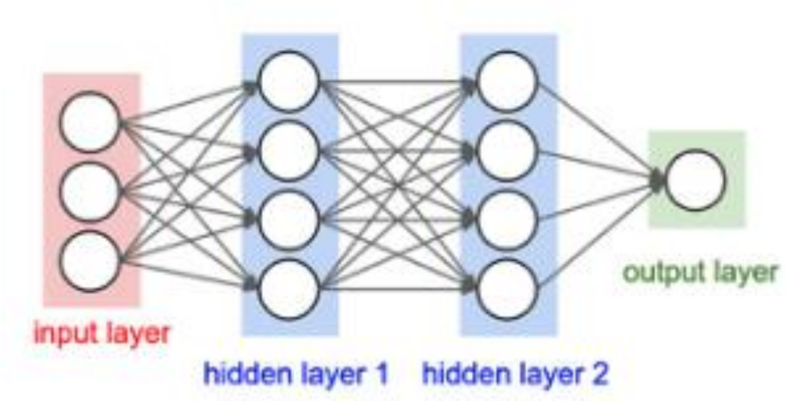
```
[-1, 0, 1]
[-1, 0, 1]
[-1, 0, 1]
```

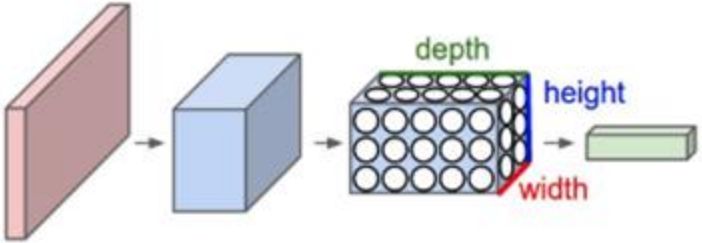


Convolutional Layers: BatchNorm and Dropout

Fully Connected vs Convolution

- Output Fully-Connected layer: One layer of neurons, independent
- Output Convolutional Layer: Neurons arranged in 3 dimensions





http://graphics.stanford.edu/courses/cs468-17-spring/LectureSlides/L10%20-%20intro_to_deep_learning.pdf

Recap: Batch Normalization

- Batch norm for **FC** neural networks
  - Input size (N, D)
  - Compute minibatch mean and variance across N (i.e. we compute mean/var for each feature dimension)

Input: $x : N \times D$

Learnable params:
$\gamma, \beta : D$

Intermediates: $\mu, \sigma : D$
$\hat{x} : N \times D$

Output: $y : N \times D$

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{i,j}$$

$$\sigma_j^2 = \frac{1}{N} \sum_{i=1}^{N} (x_{i,j} - \mu_j)^2$$

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

Recap: Batch Normalization

- Batch norm for **FC** neural networks
  - Input size (N, D)
  - Compute minibatch mean and variance across N (i.e. we compute mean/var for each feature dimension)

Batch Normalization for
fully-connected networks

$$\mathbf{x}: \mathbf{N} \times \mathbf{D}$$

Normalize $\downarrow$

$$\boldsymbol{\mu}, \boldsymbol{\sigma}: 1 \times D$$
$$\boldsymbol{\gamma}, \boldsymbol{\beta}: 1 \times D$$
$$\mathbf{y} = \gamma(\mathbf{x}-\boldsymbol{\mu})/\boldsymbol{\sigma}+\beta$$

http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

Spatial Batch Normalization

- Batchnorm for **convolutional** NN = spatial batchnorm
  - Input size (N, C W, H)
  - Compute minibatch mean and variance across N, W, H (i.e. we compute mean/var for each channel C)

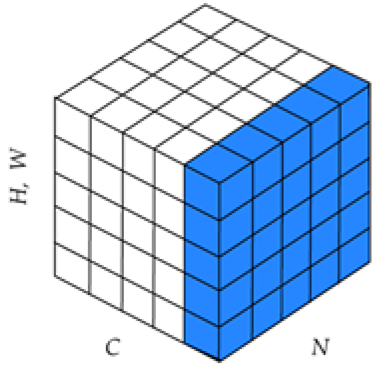
$\mathbf{x}$: N×C×H×W

Normalize ↓ (N, H, W)

μ, σ: 1×C×1×1

γ, β: 1×C×1×1

$y = \gamma(x-\mu)/\sigma+\beta$



http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

Spatial Batch Normalization

Fully Connected

- Input size (N, D)
- Compute minibatch mean and variance across N (i.e. we compute mean/var for each feature dimension)

$\mathbf{x}$: N × D

Normalize ↓

μ, σ: 1 × D

γ, β: 1 × D

$y = \gamma(x-\mu)/\sigma+\beta$

Convolutional = spatial BN

- Input size (N, C, W, H)
- Compute minibatch mean and variance across N, W, H (i.e. we compute mean/var for each channel C)

$\mathbf{x}$: N×C×H×W

Normalize ↓ ↓ ↓

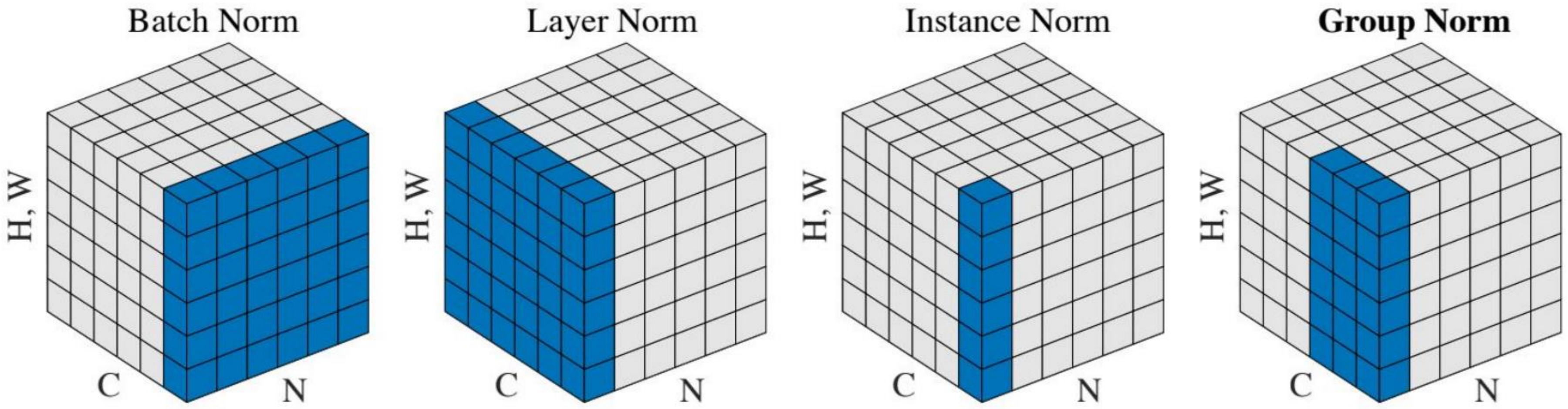
μ, σ: 1×C×1×1

γ, β: 1×C×1×1

$y = \gamma(x-\mu)/\sigma+\beta$

http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

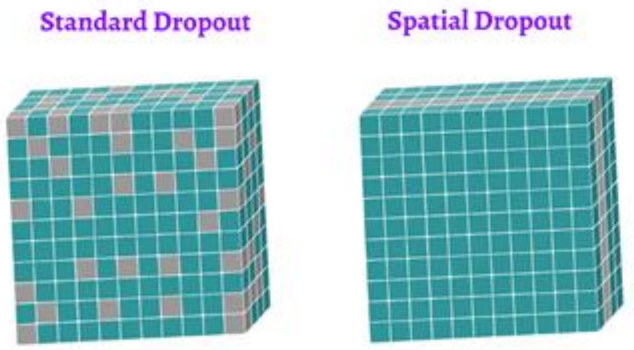
Other normalizations



http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

Dropout for convolutional layers

- **Regular Dropout:** Deactivating specific neurons in the networks (one neuron "looks" at whole image)
- **Dropout Convolutional Layers:** Standard neuron-level dropout (i.e. randomly dropping a unit with a certain probability) does not improve performance in convolutional NN
- **Spatial Dropout** randomly sets entire feature maps to zero



Dropout for convolutional layers

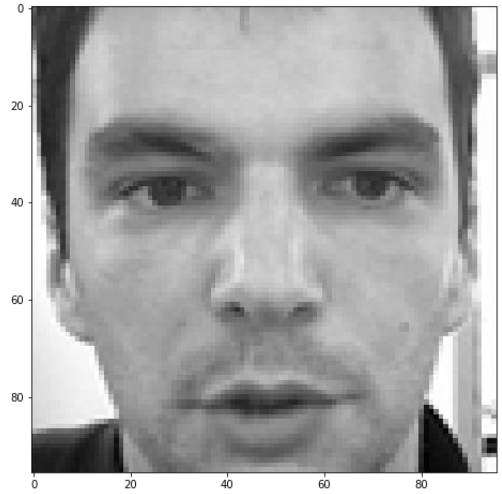
```
def dropout_mlp():
    m = nn.Dropout(p=0.5)
    batch_size = 1
    inputs = torch.randn(batch_size, 3 * 5 * 5)
    outputs = m(inputs)

    print(outputs)

    tensor([[
        -0.89,  0.37, -0.00,  0.00, -0.08, -0.00,
        0.00, -3.55,  0.00,  0.47, -0.00,  5.08,
        -0.00, -0.00,  2.63,  0.00,  0.00,  0.00,
        2.18,  1.92, -0.00,  0.66,  1.96,  0.00,
        -0.00,  -0.00,  0.00,  1.31, -1.95, -0.00,
        0.00, -4.44,  0.00, -1.07, -0.90,  -0.07,
        -3.81,  0.00,  0.23,  2.38,-2.27, -0.51,
        -3.32, -0.00, -0.65,  0.00, -0.00, -0.00,
        -0.00, -0.00, -0.61,  0.00,  0.00,  0.00,
        -1.85, -0.40,  0.00,  0.68, -0.00, -1.96,
        -0.00, -1.65,  0.00, -0.66,  3.10,  0.00,
        -0.00,  1.89,  0.00, -1.28,1.62, -0.56,
        -0.00, -0.00, -0.99]])
```

```
def dropout_cnn():
    m = nn.Dropout2d(p=0.5)
    batch_size = 1
    inputs = torch.randn(batch_size, 3, 5 * 5)
    outputs = m(inputs)

    print(outputs)

    tensor([[
        [ 0.03,  1.40,  1.76, -4.34, -0.63,
         -0.31,  2.80,  2.72, -3.00,  2.67,
          -2.31, -3.45,  0.95,  1.18,  1.18,
          -1.05,  0.74,  3.56,  0.55, -1.19,
          -0.28,  0.89, -3.36, -2.00, -0.29],
         [ 0.00, -0.00, -0.00, -0.00, -0.00,
          0.00, -0.00, -0.00, -0.00,  0.00,
          -0.00,  0.00,  0.00, -0.00, -0.00,
          0.00, -0.00,  0.00,  0.00, -0.00,
          -0.00,  0.00, -0.00,  0.00,  0.00],
         [ 0.00, -0.00, -0.00, -0.00,  0.00,
          0.00,  0.00,  0.00, -0.00, -0.00,
          -0.00, -0.00,  0.00, -0.00, -0.00,
          0.00,  0.00,  0.00, -0.00,  0.00,
          -0.00, -0.00,  0.00,  0.00, -0.00]]])
```

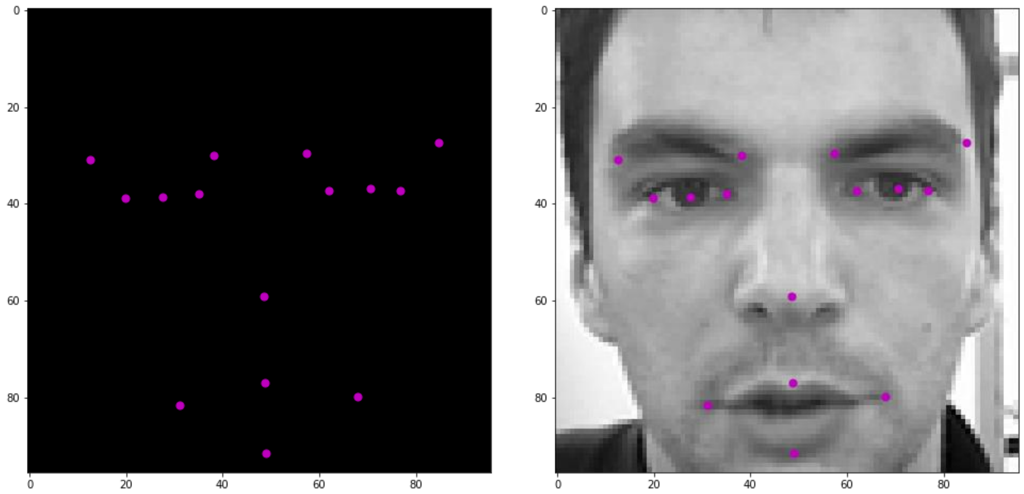
Exercise 9:
Facial Keypoints Detection

Submission: Facial Keypoints

Input:
(1, 96, 96) grayscale image



Output:
(2, 15) keypoint coordinates



Dataset:
- train: 1546 images
- validation: 298 images

Submission: Metric

Accuracy (Classification) → Score (Regression)

```
def evaluate_model(model, dataset):
    model.eval()
    criterion = torch.nn.MSELoss()
    dataloader = DataLoader(dataset, batch_size=1, shuffle=False)
    loss = 0
    for batch in dataloader:
        image, keypoints = batch["image"], batch["keypoints"]
        predicted_keypoints = model(image).view(-1,15,2)
        loss += criterion(
            torch.squeeze(keypoints),
            torch.squeeze(predicted_keypoints)
        ).item()
    return 1.0 / (2 * (loss/len(dataloader)))

print("Score:", evaluate_model(dummy_model, val_dataset))
```

Submission Requirement: Score >= 100

Good luck &
see you next week
☺